Next-generation mapping for regional smoke management and emissions inventories: incorporating underlying uncertainty in wildland fuel characterization

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* Distribution fitting
* Documentation of data gaps

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* Identified data gaps
* Probability distributions (discuss with Maureen)
* Sensitivity analysis for wildland fire emissions by region

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  + Improved emissions inventories (adding error bars to estimates)
  + Simulation modeling (draw from known distributions of fuel loadings by category)
  + Global Climate Models
  + Carbon mapping
* Identified data gaps – future research needs

**Introduction**

Mapping vegetation and biomass is increasingly relied upon to inform wildfire hazard assessments, emissions inventories, carbon mapping, and for fire, fuels and smoke planning at regional to local scales. Traditionally, single biomass values have been assigned to mapped pixels and are used as best-estimates, often based on broadly classified vegetation type. In reality, wildland fuels are highly dynamic, with high variability across time and space (Keane et al. 2012). Given their spatial variability, it would be untenable to map fuels over an entire continent at the characteristic scales at which they vary. We therefore rely on classifications of fuels such as the Fuel Characteristics Classification System (Ottmar et al. 2007) that represent a discrete set of fuel types to produce fuels maps with estimates of fuel loadings. These maps summarize fuel characteristics at relatively coarse scales (1-km pixels) and aggregate finer-scale variability to provide point estimates of fuel characteristics over the discrete set of fuel types. Underlying these classifications, however, is uncertainty in fuel estimates that is not acknowledged, much less quantified. It is not particularly informative to validate individual pixels in a continental-scale fuel map using plot-level data that may not represent the full pixel – such a validation will inevitably fail. Nor is it defensible to represent all instances of a fuel type by the same set of fuel loadings, as these vary at multiple spatial scales and are generally independent of each other.

The best practice for mapping data with inherent spatial variability is to represent the underlying uncertainty in the base fuels map. This measure of uncertainty can then be used in understanding the reliability of the fuel biomass estimates and also to evaluate how that uncertainty propagates to variability in modeled response variables, such as predicted wildland fire emissions, which are highly dependent on available fuel (REF). If it is found that emissions estimates are particularly sensitive to certain fuel categories in a major vegetation type (e.g., forest floor in boreal forests), this result could help guide future field sampling to provide a finer-scale characterization of those fuel categories. If the estimated emissions in some fuel categories are insensitive to uncertainty, then a default representation (e.g., a mean value) is likely adequate.

For many modeling projects the importance of incorporating variability is the foundation of model simulations. For example, coarse-scale dynamic vegetation models draw inputs from probability distributions in order to model stochastic processes of fire and climate (Quillet et al. 2010). Models for emissions inventories are becoming increasingly sophisticated and require corresponding complexity in input fuels datasets. Despite the acknowledged variability of fuels at multiple spatial scales (Keane et al. 2012), there are currently no national fuels products that incorporate uncertainty in estimating the biomass of wildland fuels.

In this study, we developed a geospatial database of measured fuel biomass to characterize the inherent variability of fuels across major vegetation types of the United States and Canada and to identify gaps in fuels observations. For vegetation types that had sufficient quantification of fuels by major category (e.g., canopy, shrub, herbaceous, downed wood, litter and duff), we developed probability distributions of observed fuel biomass, hereafter referred to as fuel loads, by major category. Published probability distributions will be useful for informing the first generation fuels mapping that incorporates uncertainty estimates by major fuel category. Results of this study also will help inform future sampling needs to better represent the biomass of wildland fuels.

**Methods**

*Fuel loading database*

The U.S. Fuel Loading Database was created as part of a JFSP-funded project (15-1-01-1 Mapping Fuels for Regional Smoke Management and Emissions Inventories). The database stores existing biomass measurements by major fuel category across the United States. Our team started by compiling existing databases and importing fuel loadings in a standard unit of measure (Mg/ha). Two of the existing databases (FOFEM source database and LANDFIRE reference database) were compilations of published literature and plot data. Table 1 lists the databases and provides a brief description and a source reference. We next conducted a literature review of biomass, fuel characterization and fuel consumption literature and added over 158 individual references.

Minimum standards for including observations in the database were that they: 1) contained a source reference (e.g., FIA inventory plot and sample year or journal article citation), 2) had an identifiable vegetation type (EVT Group – see below), and 3) relied on field measurements (as opposed to photo monitoring sites).

As the database was assembled, we performed a series of quality analysis and quality control measures. We first screened any records that did not have geospatial location. For each of these record, we attempted to assign a geospatial location and standardized existing location data into latitude and longitude (decimal degrees). In some cases, it was necessary to look up site locations based on site descriptions. Many records (n = 2470) had geospatial location but no assigned vegetation type or information. For these, we overlaid record locations with the EVT Groups layer in ArcGIS and assigned a likely EVT Group based on spatial location. Due to the potential assignment errors incurred by spatial assignment, we tagged each of these records as having auto-assigned vegetation types. Fuel loading values were summarized into fields defined in Table 2. In many cases, simple summations were required to create summary inputs (e.g. herbaceous load was calculated as the sum of forb and graminoid loadings and total CWD is the sum of all sound and rotten coarse wood classes).

In order to group fuel loading observations by vegetation type, we needed a standard classification. Because LANDFIRE is a common way to map fuels and vegetation, we chose to use Existing Vegetation Type Group (www.landfire.gov/NationalProductDescriptions21.php). There are 640 existing vegetation types within LANDFIRE and a total of 207 EVT Groups. Given that the objective of the database was to quantify the distribution of fuel loads within vegetation types, we opted to use a more generic vegetation classification (EVT Group), which is also provided within the LANDFIRE EVT layer, to ensure greater numbers of records within each vegetation group. It also reduced uncertainty in assigning vegetation type to each record. Most records within the database had either a general description of vegetation, a listing of major species, a Society of American Foresters or Society of Rangeland Management cover type, or a more general Forest Type (e.g., FIA plots). We developed crosswalk tables to convert cover and forest types to EVT Groups. For records that only had a general vegetation description, we individually assigned a vegetation type.

For every record that had a published source reference, we obtained the source reference and included a full citation. For quality assurance and quality control, we subsampled 30% of all source references and confirmed that entered data was correct. Most identified errors were simple rounding errors and were corrected. In a few cases, some fuel categories were missing from the inputs and were added from the published source. In other cases, fuel categories were inaccurate and corrected within the database entries. *Should we calculate any error rate?*

**Table 1**: major databases and sources.

|  |  |  |  |
| --- | --- | --- | --- |
| **Database** | **Number of records** | **Years** | **Source** |
| FFS | 128 |  | Fire and fire surrogates (McIvor) |
| FLM database | 8555 - REDUCED |  | Source data for the fuel loading model development (Keane) |
| FOFEM fuels | 1095 |  | Old database compiled to inform FOFEM fuel loading profiles (Reinhardt, Lutes) |
| Forest Inventory and Analysis Program | 15,061 | 2015 | David Chojnacky, University of Vermont– downloaded from - <http://web.gis.vt.edu/forestry/dwm/index.php> |
| LFRDB | 18,012 |  | LFRDB\_Public\_20100122.mdb |
| Natural Fuels Photo Series | 550 | 1998-2016 | <https://www.fs.fed.us/pnw/fera/research/fuels/photo_series> |

As the database was being compiled, the supported fuel loading fields were expanded to accommodate various studies and approaches. Table 2 presents the fuel loading fields and definitions within the database. Many categories are sparsely populated but are included because they are important within particular EVT Groups. For example, moss and ground lichen are important in many boreal and subboreal vegetation types but are relatively rare in other ecosystems and associated EVT Groups.

**Table 2**: Fuel loading database fields and definitions. To date, the database contains nearly 40,000 records and was designed to accommodate additional records as they become available.

|  |  |  |
| --- | --- | --- |
| **Field** | **Definition** | **Sample entry** |
| LFEVTGroupID | Unique ID for each EVT Group number | 693 |
| LFEVTGroup | EVT Group Name | Spruce-Fir-Hardwood Forest |
| sourceID | Unique ID for each source reference | 571 |
| Source | Source reference | Natural Fuels Photo Series Volume Iia, PMS 836 |
| studyPointID | Unique study point ID | 48753 |
| Plotname | Plot name if provided | AKHD 15 |
| State | State name | AK |
| inventoryYear | Inventory or sampling year | 2007 |
| veg\_notes | Vegetation description | Closed spruce-paper birch forest |
| us\_loading: Mg/ha | Understory crown loading (check) | 1.52 |
| ms\_loading: Mg/ha | Midstory crown loading (check) | 22.88 |
| os\_loading: Mg/ha | Overstory crown loading (check) | 91.32 |
| tree\_crown\_loading: Mg/ha | Total tree crown loading - sum of understory, midstory and overstory |  |
| tree\_loading: Mg/ha | Total aboveground tree biomass, including boles |  |
| snag\_loading: Mg/ha | Total aboveground biomass of dead trees, all decay classes | 13.56 |
| shrub\_loading: Mg/ha | Total aboveground biomass of shrubs | 3.43 |
| herb\_loading: Mg/ha | Total aboveground biomass of herbaceous plants including grasses and other nonwoody plants | 0.06 |
| 1hr\_loading: Mg/ha | 0-1/4 inch or 0.67 cm diameter wood | 0.9 |
| 10hr\_loading: Mg/ha | 1/4 to 1 inch or 0.67 to 2.54 cm diameter wood | 1.34 |
| 100hr\_loading: Mg/ha | 1-3 inch or 2.54 to 7.6 cm diameter wood | 2.46 |
| fwd\_loading: Mg/ha | Sum of fine wood (1, 10, 100-hr) wood |  |
| 1KhrS\_loading: Mg/ha | Sound wood 3 to 9 inches or 7.62 to 22.86 cm diameter (S1000hr wood) | 0.22 |
| 1KhrR\_loading: Mg/ha | Rotten wood 3 to 9 inches or 7.62 to 22.86 cm diameter (R1000hr wood) | 0 |
| 1Khr\_loading: Mg/ha | Sum of 1000hr wood |  |
| 10KhrS\_loading: Mg/ha | Sound wood 9 to 20 inches or 22.86 to 50.8 cm diameter (S10,000hr wood) | 0 |
| 10KhrR\_loading: Mg/ha | Rotten wood 9 to 20 inches or 22.86 to 50.8 cm diameter (R10,000hr wood) | 0 |
| 10Khr\_loading: Mg/ha | Sum of 10,000hr wood |  |
| GT10KhrS\_loading: Mg/ha | Sound wood > 20 inches or 50.8 cm diameter (S >10,000hr wood) |  |
| GT10KhrR\_loading: Mg/ha | Rotten wood > 20 inches or 50.8 cm diameter (R >10,000hr wood) |  |
| GT10Khr\_loading: Mg/ha | Sum of >10,000hr wood |  |
| cwd\_sound\_loading: Mg/ha | Sum of sound coarse wood (1000, 10,000, and >10,000hr wood) |  |
| cwd\_rotten\_loading: Mg/ha | Sum of rotten coarse wood (1000, 10,000, and >10,000hr wood) |  |
| cwd\_loading: Mg/ha | Sum of coarse wood (1000, 10,000, and >10,000hr wood) |  |
| moss\_loading: Mg/ha | Biomass of surface fuel cryptograms (arboreal moss not included) | 1.48 |
| lichen\_loading: Mg/ha | Biomass of ground lichens (arboreal lichens not included) | 0 |
| litter\_depth: cm | Depth of the litter layer (Oi soil layer) is included because many sources record this instead of loading. A generic bulk density value can be used to estimate biomass from this. |  |
| litter\_loading: Mg/ha | Litter biomass (Oi soil layer) | 4.68 |
| duff\_depth: cm | Depth of the duff layer (Oe and Oa soil layers) is included because many sources record this instead of loading. A generic bulk density value can be used to estimate biomass from this. |  |
| duff\_loading: Mg/ha | Duff biomass (combined upper and lower duff layers) |  |

*Probability distributions*

Ask Maureen to complete

**RESULTS**

1. Summary of EVTGroups and number of observations
2. Identified data gaps
3. Probability distributions (discuss with Maureen)
4. Sensitivity analysis for wildland fire emissions by region

**DISCUSSION**

1. Data needs
2. Applications
3. Implications for wildland fire emissions inventories

**CONCLUSIONS**

1. Future development (maintenance, expansion to North American fuels)